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Robust facility location decisions for resilient sustainable supply chain performance in the face of disruptions

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Robust Facility Location Decisions for Resilient Sustainable Supply Chain Performance in the Face of Disruptions

Abstract

Purpose

Facility location and re-location decisions are critical managerial decisions in modern supply chains. Such decisions are difficult in this environment as managers encounter uncertainty and risks. The study investigates establishing or moving distribution facilities in the global supply chain by considering costs, fulfillment, trade uncertainties, risks under environmental trade-offs and disruptive technologies.

Design/methodology/approach

This paper combines the possibilities and probabilistic scenarios for a supply chain network by proposing the novel Robust Optimisation and Mixed Integer Linear Programming (ROMILP) method developed under the potential uncertainty of demand while considering the costs associated with a four-tier supply chain network. ROMILP has been solved in a realtime logistics environment by applying a case study approach.

Findings

The solution is obtained using an exact solution approach and provides optimality in all tested market scenarios along the proposed global logistics corridor. A sensitivity analysis examines potential facility location scenarios in a global supply chain context.

Research limitations/implications

Logistics managers can apply the ROMILP model to test the cost-benefit trade-offs against their facility location and relocation decisions while operating under uncertainty. Future research is proposed to extend the literature by applying data from the OBOR logistics corridor.

Originality/value

This study is the first to examine sustainable dimensions along the global logistics corridor and investigate the global container traffic perspective. The study also adds value to the Middle East logistics corridor regarding facility location decisions.

Keywords: Robust Optimisation; Facility Relocation; Global Supply Chain Network; COVID-19 Disruptions; Digital Twin; Disruptive technologies.

Paper type: Research paper

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1. Introduction

Globalisation has impacted the size, scale and location of production and storage facilities in supply chain networks in numerous ways. There has been a wave of new assembly and supplier plant locations in countries such as China, India, Thailand, Vietnam, Brazil, Mexico, Turkey and some Eastern European countries due to their cheaper and more accessible raw materials supply, lower labour costs and accessibility to the extended consumer market (Marchet *et al.* 2017). At the same time, developed economies such as Japan, the UK and the USA have improved their

logistics infrastructure with much slower rates of market growth compared to that of emerging markets. This wave of location decisions has often created conflicting trade-offs in cost benefit analysis for firms such as apparel, automobile, electronic goods, branded consumer goods and other fashion goods manufacturers. If firms have considered only the ‘lower manufacturing cost’ as the prime reason for outsourcing and offshoring decisions, then the resulting supply chain structure could have led to a different network configuration and associated firm financial performance. In reality, however, in addition to low manufacturing costs, other new dimensions such as accessibility to the emerging market, growing logistics infrastructure, enhancement in affiliated technologies, improved supply chain networks, a focus on environmental concerns and sustainability in business offerings are considered to be some of the new norms of modern industry location decisions. In earlier research, Simchi-Levi *et al.* (2004: p79) defined that, “the strategic level firm location decisions in a supply chain network were aimed to have longitudinal effect on the firm performance which were aligned towards tactical decisions such as, location, capacities of warehouses and manufacturing plants and the flow of material through the multimodal logistics network”. These conventional objectives leave many questions unanswered, especially considering location decisions are driven by probable and possible situational factors that reinforce such decisions in modern global logistics situations (Sarkis *et al.* 2020). This motivates researchers to understand and examine these reinstating forces and thus contribute to the theory and practice of the logistics industry as discussed in the remainder of this paper.

1.1 Research significance

Recent uncertainty associated with COVID-19 has resulted in supply chains impacting the logistics network profoundly (Ivanov, 2020 and Sarkis *et al.*, 2020). It may challenge the conventional supply chain channel communication and degree of change in boundary conditions and

remains a mystery due to the fact that there is a need for new e-commerce technologies, which are nascent in their adoption thereof (Triblmaier, 2018). Apart from the most recent COVID-19 challenges, other comparable supply chain risks and uncertainties have similar detrimental effects on logistics networks and thus challenge the traditional assumptions associated with the supply chain and logistics network design and impose decision variables and constraints that are connected to disruptive incidents (Sarkis *et al.* (2020)).

Logistics aspects such as borderless trade environments, growing infrastructural needs, the surging demand of cost-effective solutions and existing or emerging environmental and regulatory pressures call for manufacturers and logistics service providers to redesign their supply chain network. Therefore, the global supply chain landscape is constantly changing to keep abreast of such emerging constraints and pressures. According to Melo *et al.* (2009), uncertainty is one of the most challenging problems when managing today's supply chain. However, the literature on uncertainty in location decisions in a supply chain management context reveals little (Jayaraman *et al.*, 2015). Although there are existing supply chain uncertainty and risk studies, the recent COVID-19 outbreak has created an unprecedented and extraordinary situation in the global logistics and supply chain network and therefore the need to progress supply chain resilience research and practices has become both significant and timely (Ivanov and Dolgui, 2020).

In order to respond effectively to any uncertainty, firms often need to proactively design their supply chain management network system by putting in place a well-established logistics structure that reduces the cost of the various supply chain components and improve its performance to meet the realistic constraints of the day. In addition, policy changes by the Chinese government to promote the One Belt and One Road (OBOR) initiative created significant speculation around the existing logistics players to study the feasibility options (Aliev (2016), Aoyama (2016),

Ploberger (2017) and Rakhmangulov *et al.* (2018)). Hence, this research aimed to study the feasibility of facility or Distribution Centre (DC) location or re-location in a global supply chain network, which centres around a global logistics corridor across OBOR by adopting a practical and robust approach to handle such external and internal supply chain uncertainties.

The rest of this paper is structured as follows. Section 2 surveys the literature on robust optimisation and facility location. Section 3 introduces the robust optimisation model, compares the proposed model against the existing models and sets the solution approach. Section 4 discusses the case results for the ABC Global Apparel firm and its facility location problem, while Section 5 highlights the research findings and discusses the implications based on the previous section. Finally, Section 6 highlights the theoretical contributions, key managerial contributions and recommendations with regards to the direction of future research.

2. Literature Review

2.1 Facility location decisions

Many scholars have discussed the multi-dimensional problem of firm re-location decisions in a limited application and geographical context. As early research in this direction, Moses and Williamson (1967) first discussed the firm re-location problem, as in the original location vis-a-vis re-location to alternate locations in a metropolitan environment. Brown and Gibson (1972) then proposed a plant location model, which became a much-considered model by researchers due to its simplicity and viable outcome. The Brown-Gibson model is a quantitative model which was developed to evaluate alternative plant locations using certain objective and subjective factors. However, the model was deemed unsuitable

for modern facility location decisions due to the limitations of the subjective and objective factors; this is because objective factors include cost, time, energy and distance, whereas subjective factors include policy, governance, trust and cultural aspects (Young *et al.*, 2009).

While exploring certain key anthropological studies on firm location, Wachter (1978) modelled the firm location decisions, wherein the employment aggregate changes due to the birth and death of manufacturing firms. The study also theorised that employment changes in suburban jurisdictions result only from the re-location of city plants (Wachter, 1978). Consequently, traditional location decisions were influenced by the agglomeration of industries, which ignored the total landed cost of goods to the consumer (Feller, 2008). Following from there, Erickson and Wasylenko (1980) developed a model for firm re-location and site selection decisions in suburban municipalities. In an extended study, Cordeau *et al.* (2006) considered much more than the generic facility location setup by including procurement, production, inventory, distribution and routing decisions. Zhang and Yang (2007), on the other hand, examined the facility location problem in a perishable commodities emergency system under time constraints. Recently, Benyoucef *et al.* (2013) simultaneously considered a facility location and supplier selection problem with random demand and under reliable and unreliable suppliers and solved the model by using a Lagrangian relaxation approach.

Likewise, Lu *et al.* (2017) and Kacem *et al.* (2018) presented a robust stochastic supply chain network model in the context of a case study to highlight the risk preference association and capacitated machine allocation problems. However, Gammelgaard (2019) argued that the emerging technological nature of changing the competitive advantage that a supply chain can attain by shaping its logistics strategies can be highly significant. Therefore, addressing multiple strategic decisions in logistics related problems involves multiple rules and trade-offs, which require

an integrated and robust approach to achieve better results (Petrović *et al.* 2018). The following literature section discusses some of these emerging constraints and their nature more comprehensively.

2.2 Emerging constraints

Due to the nature of disruptive technologies (Gammelgaard (2019), Liao-Troth (2012)) and changing regulations (Nilsson and Christopher (2018)), the contemporary decision variables are challenged through new objective functions of pricing on carbon emissions, on the cost of risk, on trade friction, on service level improvements and on a sustainable logistics facility apart from the conventional objectives of transportation minimisation, order shipment size reduction and inventory minimisation (Nair *et al.* (2016), Nair and Reed-Tsochas (2019)). In this context, Srivastava (2007) defined “green supply chain management (GSCM) as the integration of environmental thinking into supply chain management”. In GSCM, the environmental impacts of “carbon emissions” from transportation have been considerably attractive for research, as studies have found that almost 35% of the total transportation greenhouse gas emissions come from trucks as the only viable performed mode of transport in most developing countries (Anciaux *et al.* 2007). Emissions control is equally effective and significantly important for all stationary and non-stationary formats of a logistics system, as proposed by Sundarakani *et al.* (2010) and Jayaraman *et al.* (2015).

To adapt to the challenges faced by the global logistics industry of the new business environment, the aforementioned factors are considered to be risky and thus call for a resilient model and associated solutions. In reality, many situations that impact the business parameters are found to be uncertain, and usually no information about the probabilities are known a priori. Therefore, methodologies such as fuzzy stochastic programming and robust optimisation are applied to deal with the uncertainty (Ben Abdelaziz and Masri, 2005). For example, Yang *et al.* (2007)

studied a DC location problem in a fuzzy environment and Hasani *et al.* (2012) designed a robust closed-loop supply chain for perishable items. However, these studies have several limitations in terms of model assumptions, constraint developments and solvability, as captured in the literature (Feller, 2008, Young *et al.*, 2009 and Lechler *et al.*, 2019).

Earlier, Hassanzadeh-Amin and Zhang (2013) and Masri (2017) developed a multi-objective closed loop facility location model under stochastic demand under supply chain network theory. Likewise, Baghalian *et al.* (2013) offered a robust supply chain network design with service level against disruptions and demand uncertainty and applied the model to a case study. The risk resilience, trust and carbon emission related constraints and decisions in the proposed model complement and contribute to the theoretical development in the supply chain and logistics network theory proposed by Hearnshaw and Wilson (2013). However, the main theoretical grounding of this research is positioned on the “disruptive innovation theory” in which the innovation is more on supply chain and logistics processes rather than product or service innovation (Christensen *et al.*, 2015). The resilience driven robust decision network model is comprehensively discussed in subsequent sections.

2.3 Limitations of existing solution approaches

According to Leung *et al.* (2007), supply chain uncertainties are associated with unforeseen events and occurrences which exist with both the data and the model; despite this, extant research is limited on the robustness and robust optimal solution front. According to Sengupta (1991), robustness for stochastic programming models means to be “close” to optimal for all input scenarios, and “almost” feasible to all data scenarios. Such an approach is called “Robust Optimisation” (RO), which was first introduced by Mulvey *et al.* (1995) as a goal programming model. Subsequently,

both Mulvey and Ruszczyński (1995) and Bai *et al.* (1997) defined RO as a type of stochastic non-linear programming model in which a concave risk aversion function is added in the specification of the objectives.

Since then, RO has been used for capacitated and un-capacitated large scale facility location problems. Escudero *et al.* (1993) presented a RO formulation to handle outsourcing in manufacturing, and Gutierrez and Kouvelis (1995) developed RO models to solve a multinational corporation's production scheduling problems. The RO approach was considered as a dual-response production loading problem and provided significant performance on a two-stage stochastic programme by Wu (2006). Similarly, Castillo (2009) later developed a RO model for large scale system applications which explicitly incorporate the conflicting objectives of solution and model robustness. Additionally, Kanyalkar and Adil (2010) and La Torre (2003) applied RO in a multi-site procurement-production-distribution problem, while Behzadi *et al.* (2013) applied the RO approach in the food industry to increase safety under uncertainty. It was found in a survey by Snyder (2006) on the literature of facility location problems under uncertainty that the models developed are mainly non-deterministic polynomial hard (NP-hard) models, as discussed by Rahmaniani *et al.* (2013). In the context of downstream logistics network, in an attempt to solve the probabilistic nature of location decision in travelling sales problem (TSPs) of two echelon supply chain, Bertsimas (1989) considered a polynomial time heuristics method and an euclidean problem approach for generic facility location decisions. However, much of the TSPs are found to be theoretically saturated as depicted by Chan and Bake (2005) and they found to be very much limited to last mile delivery locations which can not be generalised across extended supply chain with multilocation decisions.

Further, fuzzy stochastic programming or the robust method has been used to model the uncertainty in facility locations for up to three echelons under different demand probability distributions in a further extension for future research (Kahramana *et al.*, 2003; Gülpinar *et al.*, 2013). In that contextual space, De Rosaa *et al.* (2013) proposed a bi-directional three-echelon facility network performance assessment under supply and demand uncertainty but left many research directions as scope for improvement. Further, a p-median approach was attempted by Snyder and Daskin (2006) when solving manufacturing facility themed location problems but was limited to several angles of analysis. In this direction of research, earlier studies conducted by Atamtürk and Zhang (2006) and Sundarakani and Van Over (2010) laid an initial grounding for dealing with uncertainty aspects in an extended four tier supply chain network robustness, whilst warranting that there were many research gaps to be addressed by future researchers.

Based on these comprehensive reviews, the research pointed out that the assessing firm's location and re-location decisions in a global logistics network to deal with robustness have been associated with many uncertainties and risk factors, which are not addressed by the existing research and therefore this study aimed to address this research gap as appropriate in the proceeding sections.

2.3 Research gap

The section underpins the theoretical side and contribution of the proposed model as compared to the other RO models discussed in the literature, as shown in Table 1.

[Place - Table 1. Features of proposed model vs. other RO models - here]

From Table 1, the facility location and allocation problem was developed by Geoffrion and Graves (1974) considering the transportation and fixed and variable facility location costs in a deterministic 3-tier supply chain. Yu and Li (2000) and Leung *et al.* (2007) developed a RO model for production planning. Next, Rahmaniani *et al.* (2013) proposed a robust model for the facility location problem mainly based on the classical Travelling Salesman Problem (TSP) by minimising the transportation and fixed facility costs through heuristics for a two-echelon supply chain. As identified in Table 1, global supply chain networks incorporating various emerging cost components, multimodal transportation constraints, allowable carbon emission aspects and trade friction are not well studied in the literature.

Gulpinar *et al.* (2013) developed stochastic and robust models for the facility location problem by adding inventory holding costs. The robust approach in Gulpinar *et al.*'s work is based on the model developed by Ben-Tal and Nemirovski (1998) as a nonlinear function of robust convex, which is solved using simulations. Although Behlazadi (2017) proposed a RO problem that is linear in terms of their production and transportation costs, the problem was focused on a New Zealand agricultural business with limited constraints. Finally, in the proposed model, an exact solution is provided through various cost minimisations under both possibility and probability for a four-echelon sustainable logistics system and thereby proposing robust resilient strategies for firms. The need of such robust resilient strategies is timely and significant due to the COVID-19 outbreak impacting the performance of the logistics industry, as captured by Ivanov and Dolgui (2020) in their position paper. Hence, in our research, the RO approach is chosen for a four-echelon dedicated facility location problem in a global supply chain on top of a Mixed Integer Linear Programme, extending the work of the existing literature and adding to that of the “supply chain network theory” based on emerging constraints and decision variables.

Hence, the paper applies a hybrid approach integrating RO with the MILP model (thus proposed as ROMILP) to handle the objectives and constraints for the facility location and re-location decisions in a global supply chain network environment. Therefore, this research contributes to the logistics and supply chain network “body of knowledge” gap by exploring the supply chain disruptions, risk and uncertainty situation in theory, and logistics industry application in practice.

3. Model description

The RO approach used in this study is based on the model introduced by Mulvey *et al.* (1995), which incorporates a goal programming structure with a set of discrete scenarios with stochastic inputs as follows:

$$\begin{aligned}
 &\text{Minimize } c^T x + d^T y \\
 &\text{s.t.} \quad Ax = b \quad (2) \\
 &\quad \quad Bx + Cy = e \quad (3) \\
 &\quad \quad x \in R^{n_1}, y \in R^{n_2} \geq 0 \quad (4)
 \end{aligned}$$

where x denotes the vector of n_1 decision variables that are not conditioned by uncertain parameters and y is the vector of n_2 control decision variables that are subject to uncertain parameters. Control variables are used to adjust the model to disruptions and changes.

Eqn. (2) presents the structural constraint whose coefficients are fixed and free of noise. Eqn. (3) denotes the control constraint for coefficients that are subject to noise. Eqn. (4), on the other hand, expresses the non-negativity conditions. In this notation, R^{n_1} and R^{n_2} denote the

set of design and control variables, respectively. Introducing $S = \{1, 2, \dots, s\}$ as a discrete set of scenarios, $\{d_s, B_s, C_s, e_s\}$ are identified as a RO model's coefficients with a probability of p_s for the realisation of each scenario as captured,

$(\sum_s p_s = 1)$. On this occasion, the optimal solution of the model will be robust with respect to optimality if it remains “close” to the optimal for any realisation of the scenario, termed as “*solution robust*”, and the solution is also robust with respect to feasibility if it remains “almost” feasible for any realisation of s , and is termed as “*model robust*”. Since it is unlikely that any solution to the problem remains both feasible and optimal for all scenarios, one is required to measure the trade-off between solution and model robustness. Taking $\{y_1, y_2, \dots, y_s\}$ as a set of control variables and $\{z_1, z_2, \dots, z_s\}$ as the error vectors under scenario s , the RO model is proposed:

$$\text{Minimize } \sigma(x, y_1, \dots, y_s) + \omega \rho(z_1, \dots, z_s) \quad (5)$$

$$\text{s.t. } Ax = b \quad (6)$$

$$B_s x + C_s y + z_s = e_s \quad \forall s \in S \quad (7)$$

$$x \geq 0, y_s \geq 0 \quad \forall s \in S \quad (8)$$

In the realisation of multiple scenarios, the objective function is defined as a random variable with a value of $\varepsilon_s = c^T x + d^T y_s$, with probability

p_s and a mean value of $\sigma(\cdot) = \sum_s p_s \varepsilon_s$ according to the linear stochastic programming fundamentals. $\rho(z_1, \dots, z_s)$ is identified as a feasibility

penalty function which is used to penalise any violation of the control constraints under some of the scenarios. Eqn. (5) presents a multi-criteria objective with the first term for solution robustness and the second for model robustness. Here, ω is used to make a trade-off between solution

and model robustness. In the aforementioned notation, the term $\sigma(x, y_1, \dots, y_s)$ is considered as the mean value $\sigma(\cdot)$ plus a constant (λ) times of the variance. This function term, with recent consideration, can be formulated as follows:

$$\sigma(x, y_1, \dots, y_s) = \sum_s p_s \varepsilon_s + \lambda \sum_s p_s \left(\varepsilon_s - \sum_{s'} p_{s'} \varepsilon_{s'} \right)^2 \quad (9)$$

As a replacement for the latest formulation, Yu and Li (2000) proposed an equivalent linear model that requires less computations compared to the previous quadratic model and adds fewer variables and constraints as shown below.

$$\sigma(x, y_1, \dots, y_s) = \sum_s p_s \varepsilon_s + \lambda \sum_s p_s \left| \varepsilon_s - \sum_{s'} p_{s'} \varepsilon_{s'} \right| \quad (10)$$

Though the model still has a nonlinear term, it can be converted to its linear equivalent by considering new non-negative variables and constraints. Yu and Li (2000) stated that a discrete linearisation approach is restricted due to the number of additive variables and constraints. Finally, they proposed the following linear framework for the RO:

$$\text{Minimize } \sum_s p_s \varepsilon_s + \lambda \sum_s p_s \left[(\varepsilon_s - \sum_{s'} p_{s'} \varepsilon_{s'}) + 2\theta_s \right] \quad (11)$$

$$\text{s.t. } \varepsilon_s - \sum_s p_s \varepsilon_s + \theta_s \geq 0 \quad (12)$$

$$\theta_s \geq 0 \quad (13)$$

The latter formulation is applied in the proposed hybrid RO method to handle any occurrence of noise in the parameters. This formulation is used to extend to facility location modelling under both uncertainty and possibility.

3.1 Model assumptions

Figure 1 represents a four-stage global supply chain network with the main components coming from the tier-1 suppliers to the plants, which produce the finished goods and distribute them to DCs for forward delivery to customers.

[Insert- Figure 1 here]

The supply chain network for the global apparel industry, as illustrated in Figure 1, comprises four players (i, j, k, l) located in different countries, representing i suppliers, j producers, k possible DCs and l customers. The ROMILP model aims to find the best choice for a DC with the best allocation of the customers. Moreover, the optimal quantity produced for each assembly plant $j \in J$ under all strategies $n \in N$ and shipments for the raw materials shipped from a supplier $i \in I$ to the plant $j \in J$, plant to DC $k \in K$, and DC to customer zone $l \in L$ under various transportation modes $t \in T$ are proposed. Finally, the deviation for the violation of the mean and control constraints are determined under the set of market scenarios $s \in S$.

In this model, it is assumed that brand manufacturers operate globally, with their suppliers, distributors and customers located in a worldwide network. A homogeneous product economy is considered implying that all manufacturers produce the same product, which is then shipped to the distributors, who, in turn, distribute the product to the end customers. The assembly line is unaffected by any ecological, operational or political interruption. However, the supply chain network is affected by the trade friction between the countries. All the players associated with the network follow a common currency. The direct ship method from a supplier to a customer is not applicable. Customer demand is not shared between the DCs. Each unit (batch) of semi-finished products/raw materials from the supplier is transformed into one finished product batch in the plant.

Carbon emissions are assumed to be produced during production and in transit from supplier to plant (by land) and from DC to customer zones (by air/land). Transportation emission is considered negligible in the transportation from the plant to the DC (as it is through water which is the cleanest mode) and other nodes of the system. Such considerations are common in the literature on Green House Gas (GHG) emissions (KPI-Team, 2016).

3.2 Model notations

Parameters:

S_i	Supply capacity of supplier i
m_j, M_j	Production capacity for assembly plant j (minimum and maximum)
q_k, Q_k	Throughput capacity for DC k (minimum and maximum)
ar_j, a_j, a_k	Advance stock of raw materials and finished product in plant j , finished product in DC k
D_l^s	Expected demand for market l under scenario s
C_i^s	Unit cost of raw material for supplier i under scenario s
A_j^{sn}	Unit cost of production in plant j under strategy n and scenario s (\$)

$\psi_{ij}^s \ \psi_{jk}^s$	Unit transport cost between i-j , j-k and k-l by transport mode t under scenario s (\$)
ψ_{kl}^{st}	
r_{kl}^t	Reliability penalty cost for transportation between k - l by transport mode t (\$)
I_i, I_j, I_k, I_l	Logistics performance index for supplier i, plant j, DC k, and customer l in scenario s
$g_{ij} \ g_j^n \ g_{kl}^t$	Unit emission penalty cost for transportation from supplier i to plant j, inside plant j under strategy n and for transportation from DC k to customer l by t mode (\$)
$e_j^n \ e_{ij} \ e_{kl}^t$	Emission for unit of production in plant j under strategy n and transportation from supplier i to plant j and from DC k to customer l by mode t (kg)
$hr_j^s \ h_j^s \ h_k^s$	Unit holding cost for raw materials and finished product in plant j plus finished product in DC k in scenario s (\$)
$f_k \ v_k$	Fixed unit cost of facility placement and variable costs of allocating DC k to market l (\$)
$\Lambda_j \ \Gamma_j \ \Pi_k$	Available space for raw materials and finished goods at plant j plus finished goods at DC k
ρ_s	Probability of occurrence for scenario s

λ	Weighting scale to decide the trade-off between cost and feasibility
ω	Weight penalty for stock-out demand
$\varphi_l^s \varphi_m^s \varphi_h^s$	Unit penalty cost for logistics friction per transaction between supplier-plant, plant-DC and DC-market (\$)
\wp	Total upper bound emission (kg)
IPC_s	Incoming Part Cost for scenario s (\$)
TAC_s	Total Assembly Cost for scenario s (\$)
IHC_s	Inventory Holding Cost for scenario s (\$)
$MMTC_s$	Multi Modal Transportation Cost for scenario s (\$)
TFC_s	Trade Friction Cost for scenario s (\$)

Variables:

x_{ij}	flow quantity of raw material between supplier i-plant j
y_{jk}	flow quantity of finished product plant j-DC k
z_{kl}^t	flow quantity of finished product DC k-market l on transport mode t
z_{kl}	total flow quantity of finished product between DC k-market l
p_j^n	production rate at plant j under strategy n
p_j	total production rate at plant j
o_k	potential DC facility k should either be opened or not, 0-1

o_{kl}	DC facility k to serve particular customer zone l or not
g_l^s	Over fulfilled stock at market l in scenario s at final stage
θ^s	Deviation for violation of mean under scenario s
δ_l^s	Deviation for violation of control constraints for market j in scenario s

3.3 Robust Mixed Integer Linear Programming (ROMILP)

Here the research derives a MILP model for the firm re-location decision problem to minimise the total cost of the supply chain network from supplier to customer.

3.3.1 Objective function

The model aims to minimise the Incoming Part Cost (IPC), Total Assembly Cost (TAC), Inventory Holding Cost (IHC), Multi Modal Transportation Cost (MMTC) and Trade Friction Cost (TFC) formulated under scenario s as follows:

$$IPC_s = \sum_i \sum_j C_i^s x_{ij} \text{ for all } s. \quad (14)$$

$$TAC_s = \sum_n \sum_j A_j^n p_j^n + \sum_n \sum_j e_j^n p_j^n \text{ for all } s. \quad (15)$$

$$IHC_s = \sum_j hr_j^s \left(-p_j^n + \sum_i x_{ij} + ar_j \right) + \sum_j h_j^s \left(p_j^n - \sum_k y_{jk} + a_j \right) + \sum_k h_k^s \left(\sum_j y_{jk} - \sum_l z_{kl} + a_k \right) \text{ for all } s \quad (16)$$

$$MMTC_s = \sum_i \sum_j \psi_{ij}^s x_{ij} + \sum_j \sum_k \psi_{jk}^s y_{jk} + \sum_t \sum_k \sum_l \psi_{kl}^{st} z_{kl} + \sum_i \sum_j g_{ij} x_{ij} + \sum_t \sum_k \sum_l g_{kl}^t z_{kl} + \sum_t \sum_k \sum_l r_{kl}^t z_{kl} \text{ for all } s. \quad (17)$$

$$TFC_s = \sum_i \sum_j \frac{\varphi_i^s}{I_i I_j} x_{ij} + \sum_j \sum_k \frac{\varphi_m^s}{I_j I_k} y_{jk} + \sum_k \sum_l \frac{\varphi_h^s}{I_k I_l} z_{kl} \text{ for all } s. \quad (18)$$

Eqn. (14) is the IPC at assembly plant j, including the costs of the raw materials or semi-finished products of the suppliers. Eqn. (15) is the Total Assembly Cost consisting of the labour, quality and manufacturing costs at assembly centre j plus a penalty for carbon emissions at plant j that vary based on the chosen environmental production strategy. Eqn. (16) is the IHC including the holding costs of keeping raw materials or finished products in a plant besides the cost of keeping the finished products in a DC. Eqn. (17) is the MMTC including the transportation cost from supplier to plant, plant to DC, and from DC to customer plus the penalty costs for the logistics emissions between an applicable route and the chosen modes of transportation, and finally the penalty cost for the uncertainty, ranked according to the selected mode and distance parameters to meet end users' demand. Eqn. (18) is the TFC which is designed to measure the logistics difficulty based on the expected overall logistics performance index of the countries concerned, which reflects the efficiency of the customs clearance process, quality of trade- and transport-related infrastructure, ease of arranging competitively priced shipments, quality of logistics services, ability to track and trace consignments, and frequency with which the shipments reach the consignees within the scheduled time; the related trade friction unit penalty cost is scenario-based and is set to increase when getting close to the customer zone.

The facility location costs are included in the fixed establishment cost and variable allocation costs for selected DC k under scenario s as formulated in Eqn. (19).

$$\sum_k f_k o_k + \sum_k \sum_l v_k z_{kl} \quad (19)$$

Then, the objective function of the ROMILP is developed as follows:

$$\begin{aligned} \text{Minimize } & \sum_s p_s (IPC_s + TAC_s + IHC_s + MMTC_s + TFC_s) + \sum_k f_k o_k + \sum_k \sum_l v_k z_{kl} \\ & + \lambda \sum_s p_s \left((IPC_s + TAC_s + IHC_s + MMTC_s + TFC_s) - \sum_{s'} p_{s'} (IPC_{s'} + TAC_{s'} + IHC_{s'} + MMTC_{s'} + TFC_{s'}) + 2\theta_s \right) \\ & + \omega \sum_s \sum_l p_s \delta_l^s \end{aligned}$$

The first term in the Eqn. (20) denotes the mean of the function, the next term represents the fixed and variable costs of facility establishment, the third term shows the variance of the objective function, and the final term specifies the model robustness with respect to the degree of infeasibility considered in the control constraints.

3.3.2 Constraints

The objective function may fall into the feasible region subject to the supply, demand, capacity, inventory, multi-modal transport, trade-friction, uncertainty, and environmental and technology constraints, as formulated in Eqns. (21) to (39).

$$\sum_k z_{kl} - D_l^s - g_l^s + \delta_l^s = 0 \quad \forall \quad l \in L \quad s \in S \quad (21)$$

$$\sum_j x_{ij} \leq S_i \quad \forall \quad i \in I \quad (22)$$

$$m_j \leq p_i \leq M_j \quad \forall \quad j \in J \quad (23)$$

$$o_k q_k \leq \sum_l z_{kl} \leq o_k Q_k \quad \forall \quad k \in K \quad l \in L \quad (24)$$

$$o_k m_j \leq \sum_j y_{jk} \leq o_k \sum_j M_j \quad \forall \quad k \in K \quad (25)$$

$$o_{kl} \leq z_{kl} \leq Q_k o_{kl} \quad \forall \quad k \in K \quad (26)$$

$$\sum_k o_{kl} = 1 \quad \forall \quad l \in L \quad (27)$$

$$o_k \leq \sum_l o_{kl} \quad \forall l \in L \quad (28)$$

$$\sum_j y_{jk} - \sum_l z_{kl} + a_k \leq \Pi_k o_k \quad \forall \quad k \in K \quad (29)$$

$$\sum_i x_{ij} - p_j + ar_j \leq \Lambda_j \quad \forall \quad j \in J \tag{30}$$

$$p_j - \sum_k y_{jk} + a_j \leq \Gamma_j \quad \forall \quad j \in J \tag{31}$$

$$\sum_l z_{kl} \leq \sum_j y_{jk} \quad \forall \quad k \in K \tag{32}$$

$$\sum_k y_{jk} \leq p_j \quad \forall j \in J \tag{33}$$

$$p_j \leq \sum_i x_{ij} \quad \forall \quad j \in J \tag{34}$$

$$\sum_j \sum_n e_j^n p_j^n + \sum_i \sum_j e_{ij} p_{ij} + \sum_l \sum_k \sum_t e_{kl}^l z_{kl}^l \leq \wp \tag{35}$$

$$\sum_n p_j^n = p_j \quad \forall \quad j \in J \tag{36}$$

$$\sum_t z_{kl}^t = z_{kl} \quad \forall \quad k \in K \quad l \in L \tag{37}$$

$$IPC_s + TAC_s + IHC_s + MMT C_s + TFC_s - \sum_s p_s (IPC_s + TAC_s + IHC_s + MMT C_s + TFC_s) + \theta^s \geq 0 \qquad s \in S \tag{38}$$

$$x_{ij}, p_j^n, p_j, y_{jk}, z_{kl}^t, z_{kl}, \theta_l^s, \delta_l^s \geq 0 \quad , \quad o_k, o_{kl} \in \{0,1\} \quad \forall \quad i \in I \quad j \in J \quad k \in K \quad l \in L \quad n \in N \quad t \in T \quad s \in S \quad (39)$$

Constraint (21) controls the demand over and under-fulfilment for each customer under each scenario. Constraint (22) ensures that the total transaction of a supplier does not exceed the maximum supply capacity. Constraint (23) limits the quantity produced to the maximum production capacity of each plant and ensures that even if one plant is activated, it works at at least minimum capacity. Constraint (24) limits the throughputs of a selected DC to be between a minimum and maximum range. Constraint (25) limits the amount of input to each selected DC to the maximum and minimum system production level. Constraints (26) to (28) ensure the dedication of a particular DC to each customer and consider that if a DC facility is opened, it should serve at least one customer; in these constraints, a new binary variable o_{kl} for assigning DC k to customer l is identified to provide the linearity condition on the model when considering a single assignment. Otherwise, this constraint can be considered with explicit nonlinearity as shown in Eqn. (40).

$$\prod_k z_{kl} = 0 \quad \forall \quad l \in L \quad (40)$$

Constraints (29) to (31) limit the capacities for holding raw materials or finished products in the plant and finished products in DC, respectively. Constraints (32) to (34) ensure the flow balance between the nodes of the logistics system, while Constraint (35) limits the amount of emissions for the logistics system including the stationary emission produced in the plant and transportation emission produced through material or product delivery from supplier to plant and DC to customer based on the maximum acceptable emission bound. Constraint (36) ensures that the total production of each plant is equal to the sum of its production by different strategies. Constraint (37) sets that the total transaction between one set

of DC and customer is equal to the sum of such transactions by different selected modes. Constraint (38) is an auxiliary constraint that provides the linearity of the RO according to Yu and Li (2000). Finally, Constraint (39) denotes the non-negative and binary variables. As described in Eqn. (40), the model includes a nonlinear component which sets the proposed model into the class of non-linear mixed integer programming. However, when adding the new variable of o_{kl} as shown in Eqns. (26) to (29) as a replacement, Eqn. (40) clearly provides the complete MILP model that can be precisely and efficiently solved through standard solvers, as reported in Yu and Li (2000), Leung *et al.* (2007), Mirzapour *et al.* (2011) and Belzahdi *et al.* (2017). The model has been solved in a real time global logistics network by applying a case study method as follows.

4 Case study

4.1 Case description and modelling

This section describes a global facility location problem for an apparel industry under various possibility states. The results are proposed for different cases of a certain decision-making process and with uncertainty incorporated in the parameters.

ABC Global Apparel's logistics system has 4 worldwide raw material suppliers: Chongqing (China), Dhaka (Bangladesh), Tirupur (India) and Karachi (Pakistan). These suppliers provide raw materials to the factories, with different capacities in Guangzhou (China) and Mumbai (India). The raw materials are usually sent to the production plants using road freight. The finished products are then shipped through sea freight

comparatively with lower carbon emissions to the possible DCs in Dubai (UAE) and Djibouti (Djibouti). Finally, the finished products are sent out from the DCs to the global market zones in Ankara (Turkey), Jeddah (Saudi Arabia) and Cairo (Egypt) by selected means of transportation. Figure 2 shows the distribution of the facility locations associated with the global apparel supply chain network.

[Insert Figure 2 here]

In this four-tiered global logistics and supply chain network, suppliers from Chongqing, Dhaka, Tirupur and Karachi have a supply capacity of 300, 150, 250 and 150 batches of raw materials, respectively. The Guangzhou and Mumbai plants have production capacities in the range of 40 to 400 batches for finished goods; they also possess fixed storage capacities for keeping raw materials and finished products at 120 and 100 batches in plant 1, and 100 and 80 batches in plant 2, respectively. The potential DCs in Dubai and Djibouti, with a transaction capacity of 450 and 400 units, can be established at a cost of \$70,000 and \$50,000 with a total variable cost of \$100 and \$130 per batch of transaction, respectively. The other parameters related to the problem can be identified in Tables 2 to 6.

In this study, the unit batch transportation cost is developed based on the distance covered in unit cost for shipment per kilometre for each location and for each mode of transportation (land, water and air) under the associated scenarios. Distance is considered as the crow flies air distance in sea freight as this is the norm for calculation. For model solvability, the air freight rate is considered to be 1.7 times more expensive than the road freight by Full Container Load (FCL). These rate ratios are commonly used by logistics service providers such as DHL and UPS for their multi-modal shipments. Further, the sea-freight rate is considered to be 0.6 times lower than the road freight rate for the same volume. It is further assumed that land transport is two times cleaner than air transport according to the carbon-emission per batch of materials for every

kilometre travelled. The sea freight emission is assumed to be zero carbon or carbon neutralised due to the nature of the shipment in model solvability aspects, as per Tables 2-4.

The data provided in Tables 2 to 6 are used for ABC global apparel logistics in all the scenarios and this dataset is configured from the literature and expert interviews. Table 2 reveals the market demand for each customer, the raw materials unit cost for each supplier, raw materials and product holding costs for each manufacturer and product holding costs at the DCs. Table 3 illustrates the production related costs including the manufacturing cost in each plant, emission amount and the penalty costs on the emissions related to two production strategies. Tables 4 and 5 describe the transportation costs in the supply chain together with the logistics emission amounts and penalty costs on those emissions for different routes and transportation options. Table 6 relates the penalty costs of logistics options under various geographical supplier, manufacturer and customer locations; these indices are identified from the World Bank's logistics performance index report (Arvis *et al.* 2018). In order to ensure maximum logistics priority on delivery to the customers, an associated penalty cost relevant to the trade friction between borders is considered while measuring the first mile and last mile delivery options that are closer to the supplier and customer zones, respectively. The unit penalty of TFC varies from \$8 to \$10 for transportation between the supplier and plant, from \$16 to \$20 from DCs to retailers, and from \$35 to \$40 for the delivery to the customers. In addition to these cost considerations, environmental consideration limits are set at an amount of carbon emissions equivalent to 3500 kgs.

[Insert Table 2 – Table 6 here]

In addition, we consider four scenarios of the most probable market growth situations as follows: (1) boom, (2) good, (3) fair, and (4) poor, with occurrence probabilities of 45%, 25%, 17%, and 13%, respectively, as indicated by Yu & Li (2000). This assumption is common for scenario

planning studies of logistics networks under realistic settings (Phelps *et al.* 2001). The ROMILP model is solved for optimality to minimise the associated logistics costs of IPC, TAC, IHC and TFC, plus facility location and allocation costs. The robust solution obtained is a trade-off between optimality and feasibility. Thus, the research proposes an optional logistics route cost structure from supplier to customer, by identifying possible DCs locations and order allocation options while meeting the demand uncertainty. The performance of the robust solution is then compared with other deterministic counterparts.

4.2. Results and discussions

All the computational results in this section are achieved by running the LINDO API 8.0-solver (Lindo Systems, 2019). In the ROMILP model, for market uncertainty, the values of λ and ω are selected as 1 and 4500 in Table 6 in order to have the best model and solution robustness trade-off as analysed. In addition, the paper considers no advance stock for the ABC facility location problem. The results are tabulated in Tables 7 to 9 and also depicted in Figures 3 to 6.

[Insert Table 7 – Table 9 here]

In Table 7, the first column shows the potential locations of DCs in k places. In the second and third columns, the aspects of opening or closing the DCs and the allocation of the DC to the best possible markets are marked by binary variables [0,1]. In the remaining columns, the number of product batches applicable to DCs while open and operational is recognised by the CO₂ emissions produced. Finally, the associated cost components for each facility in the optimised solution are measured for all scenarios. Table 8 shows the optimised flow and route. The first panel presents the optimum assignment and number of raw material batches from supplier to plant. In the next column, the production strategies are

stated as ‘1’ for a green strategy and ‘2’ for a price-efficient strategy; the production rates are identified in the plant for each strategy as optimising the related cost under uncertainty and satisfying the logistics system’s upper bound on emissions as well. Next, the number of transactions and the corresponding routes are recognised from plant to DC and DC to customers; in the latter, the transportation is selected as ‘1’ for land and ‘2’ for air with different costs, reliability, capacity and emissions. Table 8 also shows the level of carbon emissions in the supply chain. The upper panel of Table 9 shows the market demands and over and under-fulfilment conditions according to the 4 market scenarios; however, the lower part shows the total system cost with related components.

Table 9 shows that the total demand fulfilled decreases in all markets when the scenario shifts from boom to poor (1 to 4), and the same situation holds for all cost components; this trend is reversed for over-fulfilment. As shown in Tables 7 to 9, both DCs 1 and 2 are to be opened under RO with $\lambda=1$ and $w=4500$. Figures 3 to 5 present the comparative analyses of the two DCs.

[Insert Figure 3 - Figure 5 here]

Figure 3 compares the cost components related to the two opened DCs (Dubai and Djibouti) in all 4 scenarios in the optimised solution; for example, the MMTC under scenario 1 (MMTC1) costs \$314,650 for the Dubai facility compared with \$215,585 in Djibouti. However, the TAC is about the same in both facilities under all scenarios with a non-increasing trend from Scenarios 1 to 4, while the Dubai DC has an advantage over the Djibouti DC on the TFC. Figure 3 suggests that the transportation and strategic location of the DC is critical.

Figure 4 depicts the demand conditions of under and over fulfilment related to each DC when assigned to the best possible markets. In all four scenarios, under-fulfilment is found to be the highest in the Dubai facility when there is a boom (scenario 1). Over-fulfilment, on the other

hand, is more pronounced in scenario 4 for the Dubai DC. Figure 5 compares the two facilities from the environmental related characteristics including logistics and production emissions. When we again compare Djibouti DC with Dubai DC for environmental considerations, Djibouti seemed to be a better trade-off compared to Dubai; however, the volume of business connected to the Dubai DC enables the preference.

[Insert Figure 6 here]

Figure 6 provides a trade-off between the solution robustness and model robustness, whereby increasing the stock-out weight penalty diminishes the under fulfilled demand, although the total cost variance increases. This is done to ensure the robust solution feasibility and optimality. However, the values of $\lambda=1$ and $\omega=4500$ are a superior trade-off as the under-fulfilment percentage is 6% with a mean variance of \$63,645 from the total cost of \$1,766,000.

[Insert Figure 7 here]

In Figure 7, the effect of changing the weight on the facility location and allocation decisions is analysed for three values of w (2700, 2900, and our selected 4500). The results present different facility decisions in the three examples that prove model sensitivity to the favoured stock-out risk penalty parameter of $w=4500$. Overall, the Dubai DC benefits from a sustainable business standpoint connecting all the sources and destinations.

4.3. Comparison of results performance

The results of the proposed RO model are compared against 4 deterministic approaches. In all instances, the demands are completely satisfied, and an optimal solution is found for the scenarios. However, the RO model yielded a smaller than expected cost value (see Table 10).

[Insert Table 10 here]

From Table 10, the expected value of the total cost for the robust solution of the 4 scenarios compared to the 4 deterministic solutions (D1-D4) is the lowest. In addition, the RO solution is closest to the optimum in terms of the total cost as compared to the other most probable solutions under Scenarios 1 and 2 that have a total probability of occurrence of 70%. In this comparison, the costs are calculated based on the total cost of the model, including the IPC, TAC, MMTC, TFC, variable and fixed facility costs plus the shortage and overage costs. The unit shortage cost is set at $w = 4500$ in line with the RO model and the unit overage cost at the final stage is set at 20% higher than the maximum unit holding cost in the DC. While the total saving varies for the scenarios, the RO solution clearly outweighs the rest.

5. Managerial Implications

As demonstrated in Table 7 and Figure 3, for the optimal solution, both DCs are chosen to be opened in the proposed locations. In the optimised allocation, the Dubai DC is selected to serve markets in Turkey by air. The Djibouti DC is assigned to the Saudi Arabian and Egyptian markets using land transport. Such an approach of facility location and allocating markets by considering λ and ω reduces the risks of escalating costs and of not fully satisfying demand, as shown in Table 10. The model and solution thus enable logistics service providers and business organisations that are networked under these supply and market conditions. The research also supports supply chain planners to better plan for

cost, environmental friendliness, trade friction conditions, and geo-political risks and uncertainties. Figure 8 shows the optimised network design, logistics strategies and transport modes.

[Insert Figure 8 here]

Figure 9 exhibits the current global container traffic captured from a live Dubai Trade container traffic system, highlighting the red spots of shipment vessels that move along the OBOR corridor. Other implications recommended for managers are: practice green target and related alternative production/transportation policies, achieve trade-off between reliability, cost, risk and green environment compliance for facility location decisions, and identify an optimal solution based on various multi-objectives in terms of the expected total cost saving while satisfying the demand in an uncertain market.

6. Conclusion

This research paper has proposed a Hybrid RO and MILP method linking the social constraints with the modern supply chain constraints under possibility and probability situations. Supply chain managers can use ROMILP to test the cost benefit trade-offs with respect to the green facility location and supply chain cost decisions when operating under uncertainty.

6.1 Theoretical contribution

The model can facilitate decision making aspects for the possibility of establishing or relocating a distribution facility in the global supply chain network. This is significant because this paper combines the possibilities and probabilistic scenarios for a supply chain network by proposing

the ROMILP method. As a result, this research challenges the traditional assumptions associated with the supply chain network design and imposes decision variables and constraints that are connected to disruptive robust optimisation. Thus, the research contributes to the supply chain and logistics network theory by the addition of new dimensions, variables and constraints under disruptive conditions. A case study has been solved on a global supply chain network along the OBOR corridor and is able to understand the cost implications of the current situation and to anticipate the impact of ongoing OBOR developments. Despite the supply chain network side theoretical contribution the research add value to the ‘disruptive innovation theory’ to prepare resilient strategies at the face of uncertainty as follows.

Earlier, Kaplan (1964) said, "A new theory requires its own terms and generates its own laws: the old concepts are not merely reorganized, but reconstituted, the old laws not just connected, but given a new meaning" (p. 297). In practice, technological adoption applications under disruptions in supply chains have the capability to challenge some existing business theories and to add a wholly new dimension to the existing theory, as discussed by Kaplan (1964). For organisations to be able to extend their competitive advantage, resilience business strategies, resource allocations, new facility arrangement and infrastructural arrangements are of paramount importance. The evolution of logistics networks and process innovation are a transformative process. According to Industry 4.0 disruptions, the supply chain-wide stakeholder reengineering and transformation would be required for effective blockchain implementation (Zhu *et al.*, 2018). This has been echoed by Dolgui *et al.* (2020), who state that blockchain adoption in supply chains has the capability to change some of the traditional constructs, and the relationships in the existing theory may have to be revisited to determine their applicability. As discussed, the article is grounded on “disruptive innovation theory” in which the innovation is more on supply chain processes rather than product or service innovation (Christensen *et al.*, 2015). As we anchored the research

on “disruptive innovation theory”, the research has added to the theoretical body of knowledge and opened up the door for academics and practitioners to extend further research in this space. Especially during the COVID-19 pandemic, where the industry growth formulae have been changed and disrupted, the requirement and benefits of this research are multi-faceted, critical and essential.

6.2 Practical contributions

Since the OBOR developments are currently highly fragmented across Asian countries due to geo-political conflicts and challenges, the impact of the proposed corridor and expected benefits are yet to be measured. Therefore, the research proposes a number of recommendations which could be used by practitioners to make decisions under uncertainty and for policy makings. Because emerging markets possess greater market opportunities, the potential benefits of disruptive innovation are substantial if appropriately reaped. Since only a few organisations globally are advanced in implementing new data analytics (Fosso Wamba, 2019; de Camargo Fiorini *et al.*, 2019) and blockchain related digital twin technology initiatives, the recommendations can be useful for other companies in the Middle East and elsewhere who wish to implement such robust disruptive models that can aid logistics decision making aspects in their business processes. As we see a wave of digital transformation moves in the vertical logistics industry, the need for robust resilient decision-making tools or solution approaches are essential. C-suite executives of third-party logistics firms need timely intervention, as well as changes in strategies, planning and operational execution based on the cost, service and risk hedged realistic actions and supply chain location decisions.

6.3 Future research opportunities

This research can be extended by adding capacity considerations on storage and related warehousing, transportation loads and also by considering political risks and trade barriers of the OBOR corridor. Thus, the research expands future research directions to be able to assess how the proposed OBOR mentioned in global container traffic would impact the current container traffic both worldwide and for the countries participating in the OBOR corridor mega project. Because this research addresses one of the most important aspects of the complex robust logistics network optimisation in practice, the article focuses on how non-linear thinking in terms of OBOR decision variables and related adaptive ecosystems make this research more innovative, relevant to the industry and futuristic. Thus, the novelty and contributions of this research create pathways for future researchers in this era of disruptive supply chain digitalisation.

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Table 1. Features of proposed model vs. **existing** RO models

Author (year)	Objective Function Components								Other	Constraints								Assumptions				Model	Solution
	Inventory Cost	Transportation Cost	Production Cost	Incoming Parts Cost	Workforce Cost	Emission Cost	Fixed Facility Cost	Var. Facility Cost		Supply & Production	DC throughout put	Nodal Flows	Storage	Production	Workforce/Machine	Emission	Other	Possibility	Probability	No. of Echelons	Uncertainty		
Geoffrion & Graves (1974)	-	Single	-	-	-	-	✓	✓	-	✓	✓	-	-	-	-	-	1 DC dedicated to each client	✓	-	3		MILP	Exact
Yu & Li (2000)	✓	Single	✓	-	-	-	-		-	✓	-	-	✓	✓	-	-	-	-	✓	3	Demand, Stock and Production Cost	RO	Exact
Leung et al. (2007)	✓	-	✓	-	✓	-	-		-	✓	-	-	✓	✓	✓	-	Max. Quota, Customer Preference	-	✓	3	Demand, Production, Inventory and Labour Costs	RO	Exact
Rahmani et al. (2013)	-	Single	-	-	-	-	✓		-	-	✓	-	-	-	-	-	-	✓	✓	2	Demand, Transportation cost	RO MILP	Heuristic
Gulpinar et al. (2013)	✓	Single					✓		-		✓						n DC dedicated to each client			2	Demand, Stock	RO MINLP	Heuristic
Behzadi et al. (2017)		Single	✓		✓			✓		✓				✓	✓		-			3	Demand, stock and transportation	RO	Exact
Proposed Model	✓	Multi modal	✓	✓	-	✓	✓	✓	Trade Friction Cost	✓	✓	✓	✓	✓	-	✓	1 DC dedicated to each client	✓	✓	4	Demand, Stock, Unit cost of part, Production, Inventory and Logistics performance penalty cost	RO MILP	Exact

Table 4. Transportation unit costs under different scenarios, emission and emission penalty costs between supplier, plant, and DC												
Scenario	Unit production cost (\$)				Unit emission penalty cost (\$)				kg CO ₂ e -batch			
	Strategy				Plant				DC			
	1	2	1	2	1	2	1	2	1	2	1	2
	1	1	2	2	1	1	2	2	1	1	2	2
	1	2	1	2	1	2	1	2	1	2	1	2
1	650	600	675	620								
2	600	540	625	575								
3	580	530	600	550	85	110	85	110	1.9	2.4	1.9	2.4
4	570	520	575	525								

Table 5. Logistics performance indices and friction penalty costs under different scenarios											
Scenario	Supplier				DC			Market			
	1	2	3	4	1	2		1	2	3	
	Indexes				Penalty cost (\$)			Plant			
	3.52	2.75	3.1	2.85	3.78	2.4		1	2	3	4
	1	2	3	4	1	2	3	1	2	3	4
1	1	20	26	23	25	38	59	1	75	83	88
2		18	23	21	22	34	53		70	77	82
3		17	22	19	21	32	50		67	74	78
4		16	21	18	20	30	47		65	72	76
1	2	23	29	26	28	43	67	2	119	131	139
2		21	26	23	25	38	60		110	121	128
3		19	25	22	24	36	57		105	116	123
4		18	23	21	23	34	54		102	113	120

Table 7. Facility location optimal solutions and associated costs

F, k	Open/ Close	Assigned To			Amount (units)	CO2 (kg)	S/n	Associated variable costs on DC (\$)											
																		DC	
																		Variable	
																		Cost.	
Market			DC																
1	2	3																	
1	1	1	0	0	350	2034	1	98500	115000	257000	255500	314650	215585	47140	80283	35000	45500		
							2	92900	108800	239750	239750	303200	207660	43086	73437	35000	45500		
2	1	0	1	1	350	1426	3	88000	104500	232500	231000	298100	201325	41059	70015	35000	45500		
							4	86000	100550	228250	222250	292550	198705	39361	67183	35000	45500		

Table 8. Optimal production and shipment strategy

Ship from i to			Strategic			Ship from j to			Multimodal shipment				
j			production in j			k			from k to l				
Supplier i	Plant j		Strategy n	Plant j		Plant j	DC k		DC k	Market l			
	1	2		1	2		1	2		Mode	1	2	3
1	300	0	1	300	0	1	300	0	1	1	0	0	0
2	0	0							2		350	0	0
3	0	250	2	0	400	2	50	350	1	2	0	165	185
4	0	150							2		0	0	0
CO ₂ (kg)	1530			408			N/A				1930		

Table 9. Optimal total costs breakdown and over/under fulfillment

Sn	Demand				Under-fulfillment/Over-fulfillment (U_f/O_f)					
	Market				1		2		3	
	1	2	3		U_f	O_f	U_f	O_f	U_f	O_f
1	400	188	200		50	0	23	0	15	0
2	350	161	185		0	0	0	4	0	0
3	280	150	160		0	70	0	15	0	25
4	240	143	130		0	110	0	22	0	55
Cost breakdown (\$)										
	IPC	TAC	MMTC	TFC	IHC	Fixed (facility)	Variable (facility)	Mean var. penalty	Demand var. penalty	Total cost (\$)
1	213500	512500	530235	127423.2	0	120000	80500	0	396000	1980158
2	201700	479500	510860	116523.2	0	120000	80500	55070	0	1564153
3	192500	463500	490675	108217.1	0	120000	80500	138810	0	1594202
4	186550	450500	491255	106544.4	0	120000	80500	202150	0	1637499

Table 10. Comparison between proposed robust and most probable deterministic solutions

	Total cost under scenarios 1 to 4 (\$)				Expected cost (\$)	RO expected cost saving (\$)
	Sn1	Sn2	Sn3	Sn4		
D1	1796280	1715493	1693948	1660657	1741056	32583
D2	1991669	1494147	1475644	1446121	1708643	171
D3	2212815	1736623	1226562	1212427	1796053	87581
D4	2408558	1935387	1433302	1056457	1948699	240226
RO	1981590	1502283	1483498	1453779	1708472	-

Note: D1-D4 denote the four deterministic approaches.

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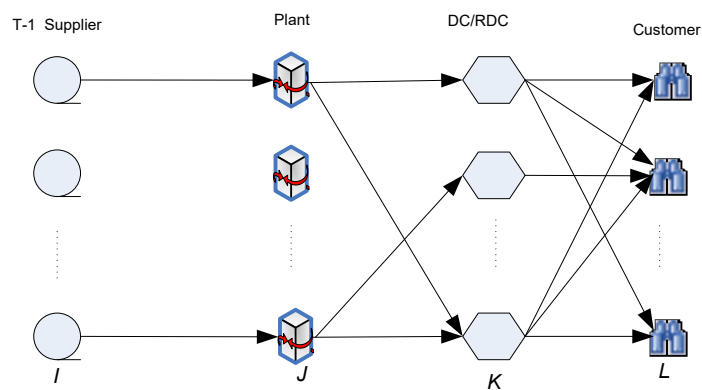


Figure 1. A typical 4-echelon global supply chain network

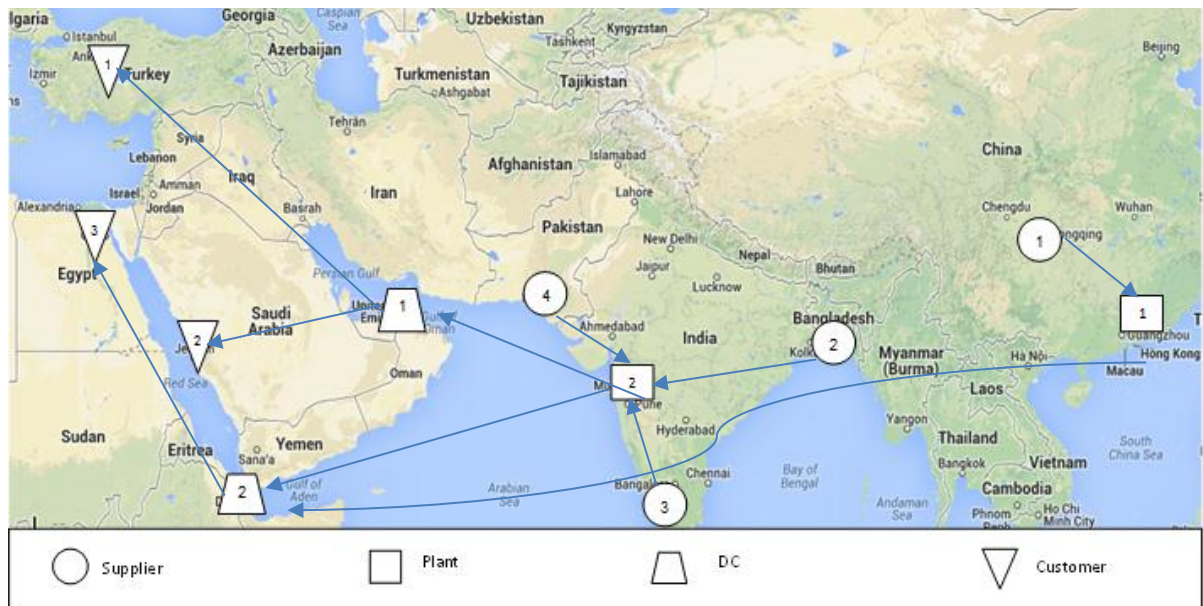


Figure.2. ABC global apparel supply chain network with possible DCs

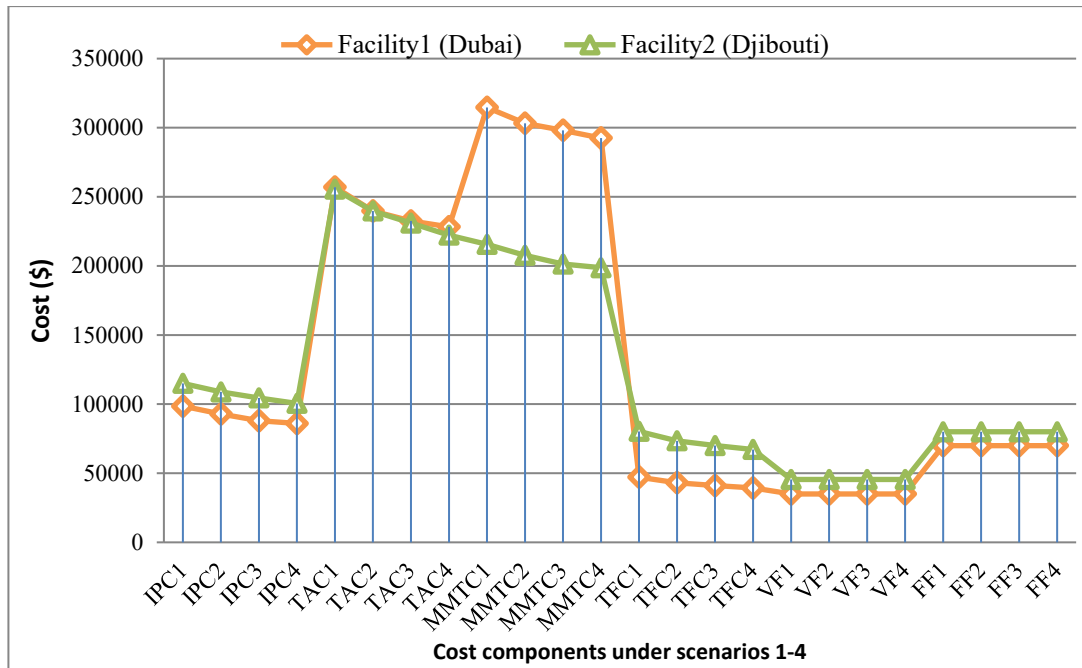


Figure 3. Optimal cost components for selected DC locations for scenarios 1 to 4

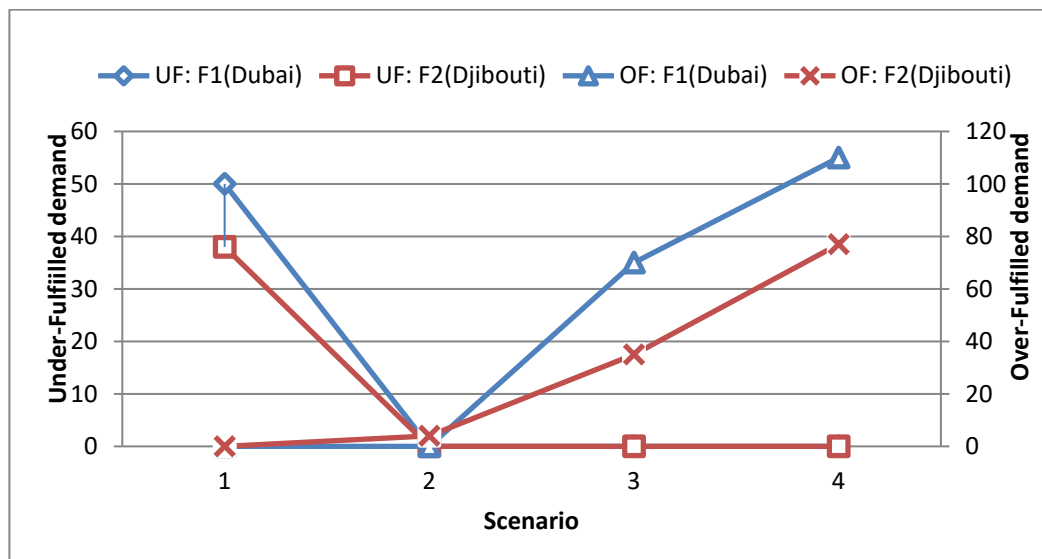


Figure 4. Optimal under/over-fulfillment in each market by selected DCs for scenarios 1 to 4

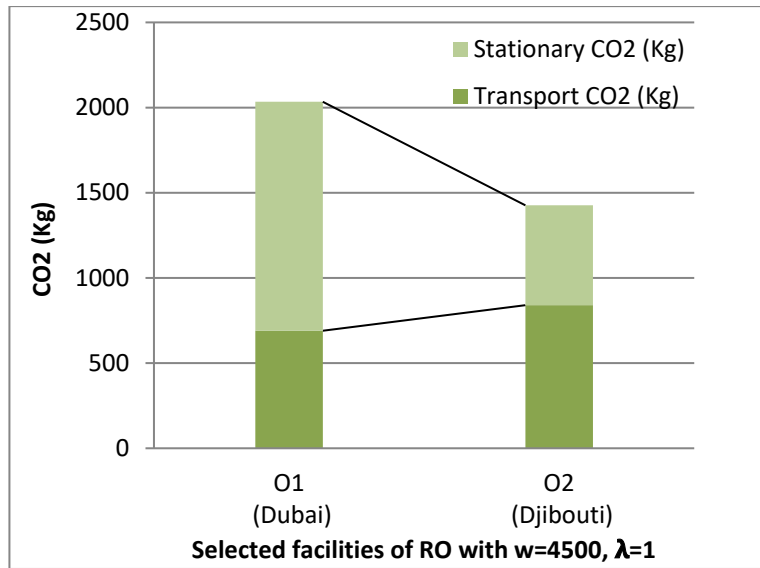


Figure 5. Transportation and stationary carbon emissions produced for each selected DC

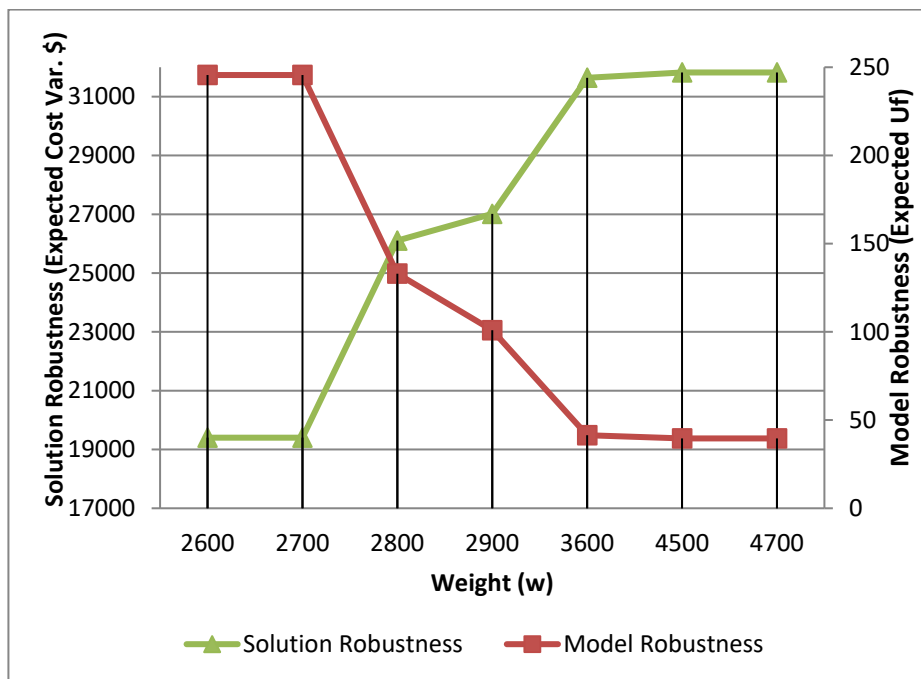


Figure 6. Trade-off between solution robustness and model

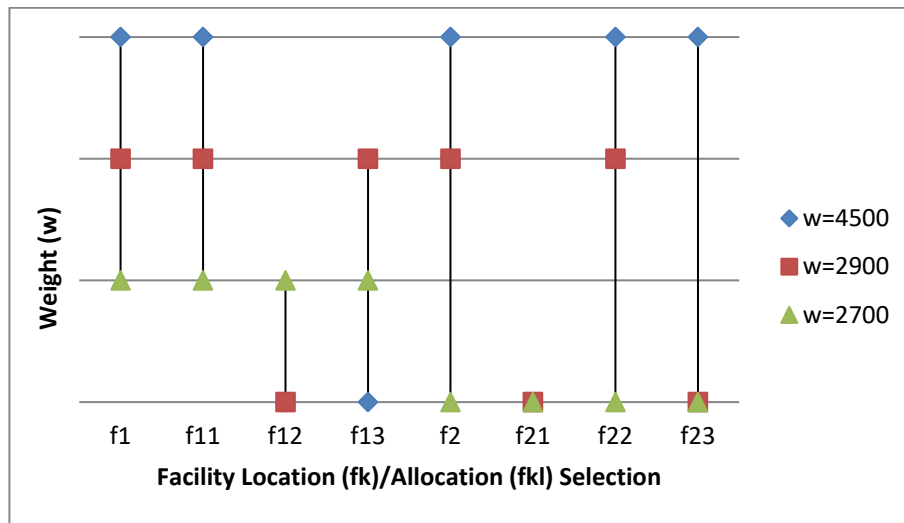


Figure 7. Sensitivity analysis of facility decisions to favored model robustness

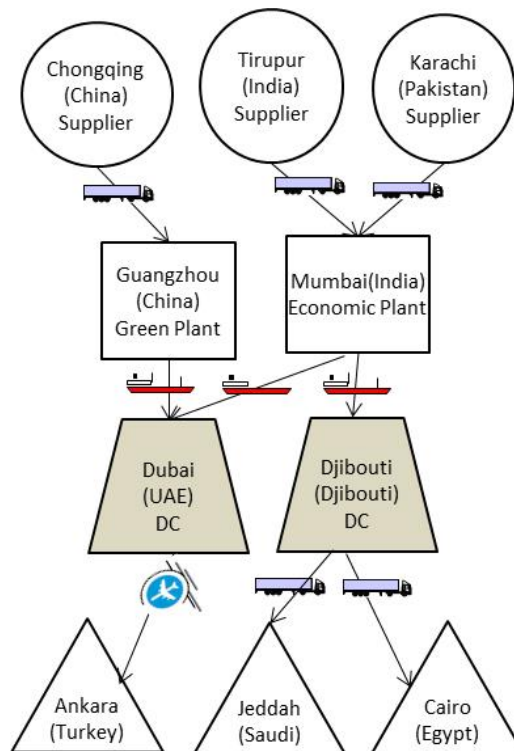


Figure 8. Design of optimized ABC global apparel supply chain network with selected DC's

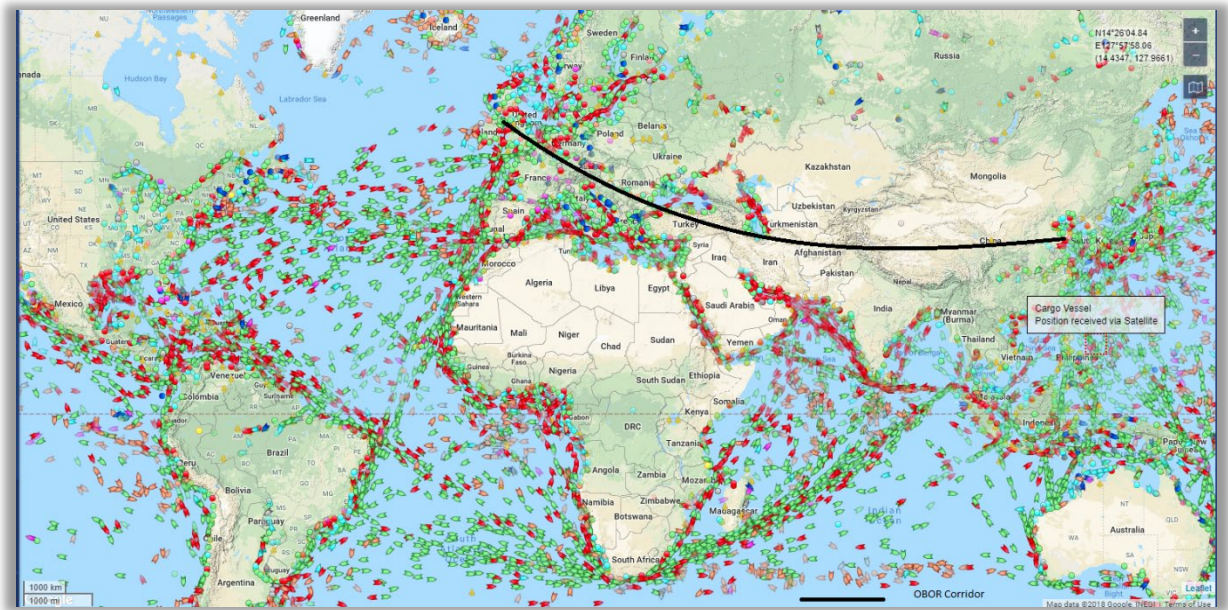


Figure 9. Proposed One Belt One Road (OBOR) corridor drawn by the author on a global live container traffic as on 18 June, 2019 (Source: Dubai Trade and Dubai Customs)